# Hydraulics Simulation Using Neuro-Numerical Modeling Approach

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**Abstract**

A new computational procedure "Neuro-Numerical Modeling" using the response relationship between boundary forcing and those locations (computational nodes) with numerical simulation is presented. Artificial neural networks (ANNs) were used to conduct nonlinear and time-delay analyses after the knowledge base, which generated from the outputs of numerical simulation. To demonstrate this approach, two numerical simulation examples were presented. First example was a tidal wetland simulation of water surface elevation and velocity (RMA10) at a site on the Hudson River, New York. A flood sediment control project in Gauadalupe River, California was the second example which links between sediment numerical model HEC-6W and ANNs. The results show both Elman-Jordan recurrent network and time-lagged network are good selected algorithms to simulate these systems.

**Introduction**

Numerical simulation of flows and other processes occurring in water has now matured into an established and efficient part of hydraulics analyses. Moreover, through the many innovations of modern computational techniques, such as hydroinformatics, numerical hydrodynamics models are now becoming more accurate and reliable tools for analysis, design and management. However, the models from coastal, estuary, and river hydraulic systems with hundreds of thousands of nodes are becoming increasingly common. These models make heavy demands on computing capacity. The great divergence between the response-time requirements and the computational-time requirements needs to reduce the time required to simulate the impact of input events on hydraulics of the modeled flow system.

Another alternative is based on the analysis of all the data characterizing the system. A model can then be defined on the basis of connections between the system state variables with only a limited knowledge of the details about the "physical" behavior of the system. To improve the modeling quick response, an intelligent computational method, such as artificial neural networks (ANNs), is considered as an alternative aspect. A new approach, neuro-numerical modeling, uses the numerical model as the simulator to generate the knowledge base for the response variables of desired locations (nodes) in the modeling domain.

## Artificial Neural Networks (ANNs) and Neuro-Numerical Modeling

Artificial Neural Networks (ANNs) is a type of biologically inspired computational model based on the functioning of the human brain. ANNs is a set of real and artificial neural networks capable to learn and adapt, generate data, and distribute processes. It is a modern computational technique for solving many complex nonlinear and dynamic problems through learning and reasoning processes. ANNs have used several algorithms; particularly, time-lagged neural networks and partial recurrent networks, both are suitable to obtain highly accurate solutions for solving spatial and temporal forecasting problems. Hsieh (2002) summarized the basic concept and performance evaluation of training processes for ANNs. The detail theory development for the algorithms is referred to Principe et. al. (1999) and Haykin (1994).

A new approach, neuro-numerical modeling (Figure 1), uses the numerical model as the simulator to generate the knowledge base for the response variables of desired locations (nodes) in the modeling domain. For example, the salinity at a number of downstream locations (numerical model nodes) can be used to represent the outputs from the ANN model while the boundary conditions (freshwater inflow, source tide, and wind stress) can be used as the input variables of the ANN model. During the learning process of the ANN model, a series of numerical simulations with different combinations of input variables is needed. Usually, weeklong numerical simulations can be represented, as long as the typical and extreme variations in the system are included within the series of simulations. It should be noted that the reliability of the

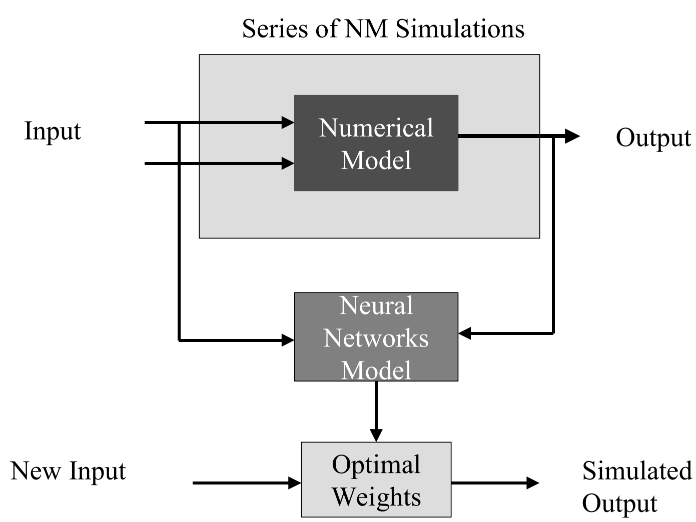


**Figure 1. A neuro-numerical model approach**

entire system is heavily dependent on a well-validated (field data verification) numerical model. The advantage of this approach is once the response of ANNs has been established, the simulation process can be conducted directly from ANNs model while providing the new input series. The performance of ANN models will be improved once new significant information enters the knowledge base and ANNs has been retrained.

**Linkage of a Tidal Wetland Numerical Model (Hsieh, Letter, and Brown 2002)**

**Numerical simulation model.** The numerical hydrodynamic model, TABS-MDS, was used as a simulator to generate the knowledge base of the ANN model. TABS-MDS (Multi-Dimensional, Sediment) is a finite element, hydrodynamic model. It is based on RMA10, a model written by Ian King of Resource Management Associates. It is capable of modeling turbulent, sub-critical flows using 1-D, 2-D, and/or 3-D elements. It is also capable of modeling constituent transport. This includes modeling salinity, temperature, and/or fine-grained sediment. The model is capable of coupling the spatial density variation induced by concentration gradients in the constituent field to the hydrodynamic calculations. This enables the model to simulate phenomena such as saline wedges in estuaries. The model has features that permit the simulation of intermittently wetted regions of the domain, such as coastal wetlands. The local wetland model is presented in Figure 2.

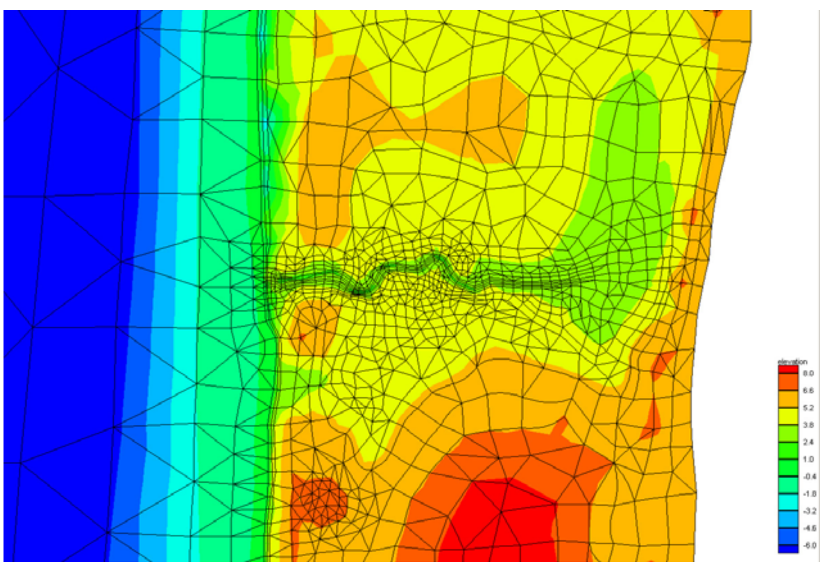


**Figure 2. The detail of the TABS-MD wetland model**

Wetlands are transition areas between dry uplands and open water environments: they are neither land nor water – but they are both land and water. Understanding of the variation of surface elevations, water depths, and velocities during different boundary forcings is particularly important to understanding the ecosystem response. The study site (Schodack Houghting Island) is in the upper portion of the Hudson River with boundary forcings of tide from Montauk Point and Sandy Hook (Atlantic

Ocean) through the New York Harbor. A constant river flow of 50000 cfs from the Hudson River was used. A 2D numerical model (9379 elements and 29336 nodes) using TABS-MDS was developed for calculating the tidal hydrodynamics.

The model ran a one year simulation with a 30-minute time step and saved 10 locations for water depth/surface elevation (one location is in the main stem) and 2 locations for x and y velocity components. The approach of this investigation was to use a portion of the information to develop the ANNs model and use the remaining part of the numerical results to check the generalization (performance) of ANNs.

**Knowledge base generation.** The foundation for ANNs is pattern recognition, which means performance depends on how extensively patterns are involved in the knowledge base. In other words, the total length of the variable time series is not a significant factor contributing to the generalization after the system simulation time series has experienced certain extreme conditions. The boundary forcing used for both the numerical hydrodynamic model and ANNs model includes two water surface elevation boundary conditions on the model domain. With tidal harmonic analysis, sixteen significant tidal constituents were determined. These include ten semi-diurnal components (*M2, S2, N2, K2, T2, L2, 2N2, ν2, λ2* and *μ2*) and six diurnal components (*K1, O1, P1, Q1, M1, and J1*). The former components have periods around 12 hours and latter component have periods around 24 hours. These significant components form a tidal record with a neap-spring cycle. Therefore, a one-year period can be divided into 26 sub-neap/spring tidal periods. This study uses three sub-periods for training, three sub-periods for cross-validation, and the remaining period for testing. Three methods; namely, random selected period, statistics parameters (mean and standard deviation), and tidal energy level (spectral analysis for time-frequency series) are selected to determine the most significant patterns among the sub-periods.

**Demonstration example.** The performance of system response due to boundary tidal forcing for ANN modeling is somewhat different from numerical simulation. Basically, the accuracy is reduced if the response parameters (such as velocities) are different. In order to test the similar response between these two systems, a local slope concept is introduced. It means if the local surface slopes around a node can be estimated correctly, then it is possible to estimate the velocities for that node using ANNs modeling. This indirect estimation for velocities (or other parameters) is called a multi-stage ANNs modeling approach. A demonstration example using the numerical simulation from four directions of surface elevation from two nodes away for a particular node in the tidal wetland site is presented.

A four-input/two-output system (surface elevations at south node as one of input series: Figure 3) is established using ANNs with Jordan-Elman recurrent neural networks training (Figure 4) and randomly selected period training setting. Good agreement is obtained (CCvx = 0.930 and CCvy = 0.934) for training and less accurate for testing (CCvx = 0.830 and Ccvy = 0.834). The results of testing for y-components are shown in Figure 5.

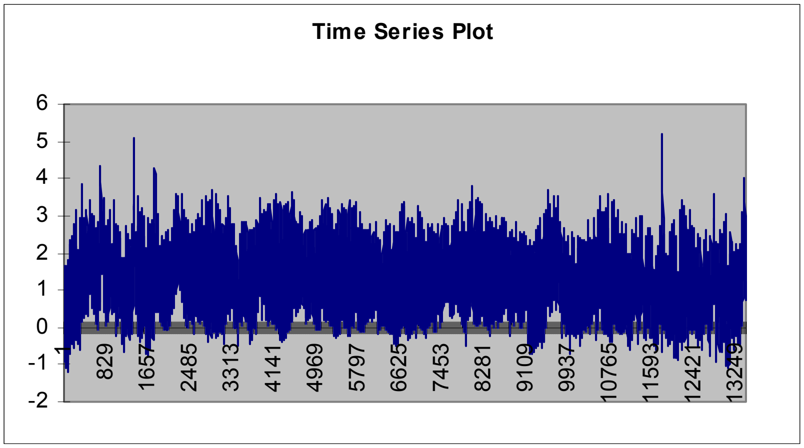


**Figure 3. Surface elevation (ft) from southern numerical node**

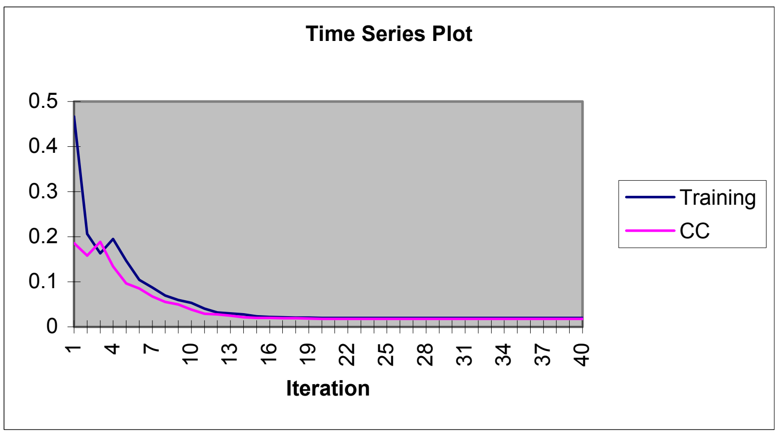


**Figure 4. Mean square errors of training and cross-validation processes for first 40 iterations**

**Linkage of a Numerical Sedimentation Model (Hsieh and McComas 2002)**

**Numerical simulation model.** The HEC-6W one-dimensional numerical sedimentation model was used to make predictions in this study. The program produces a one-dimensional model that simulates the response of the riverbed profile to sediment inflow, bed-material gradation, and hydraulic parameters. The model simulates a series of steady-state discharge events, their effects on the sediment transport capacity at cross sections and the resulting degradation or aggradation. The program calculates hydraulic parameters using a standard-step backwater model.

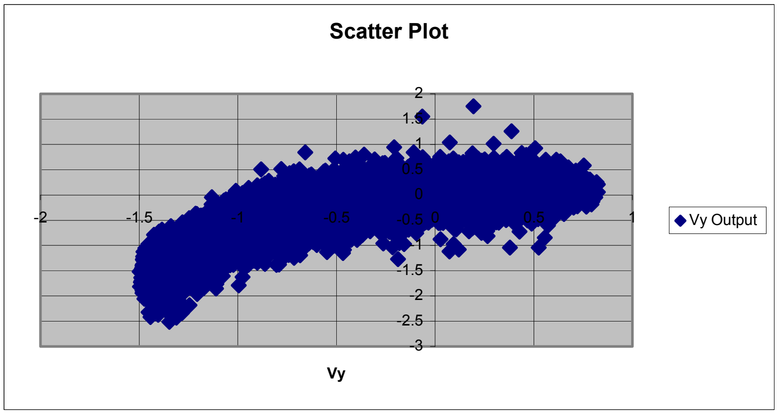


**Figure 5. Testing results y-component of velocity using surface slope approach**

HEC-6W is a state-of-the-art program for use in mobile bed channels. The numerical computations account for all the basic processes of sedimentation: erosion, entrainment, transportation, deposition, and compaction of the bed for the range of particle size.

**Guadalupe numerical sedimentation model.** The Guadalupe River is located in Santa Clara County, CA. Figure 6 shows the major features of the Guadalupe River basin. The reach of the Guadalupe River studied in the report (Copeland and McComas, 2002) extends 3 miles, between Interstate Highway 280 on the south and Interstate Highway 880 on the north. This reach encompasses much of downtown San Jose. The USACE project proposed for this reach of the river is a multipurpose project including both recreation and flood-control benefits. The objective of this numerical sedimentation study was to evaluate the potential impact of the Guadalupe River flood-control project on channel stability in terms of channel aggradation and degradation.

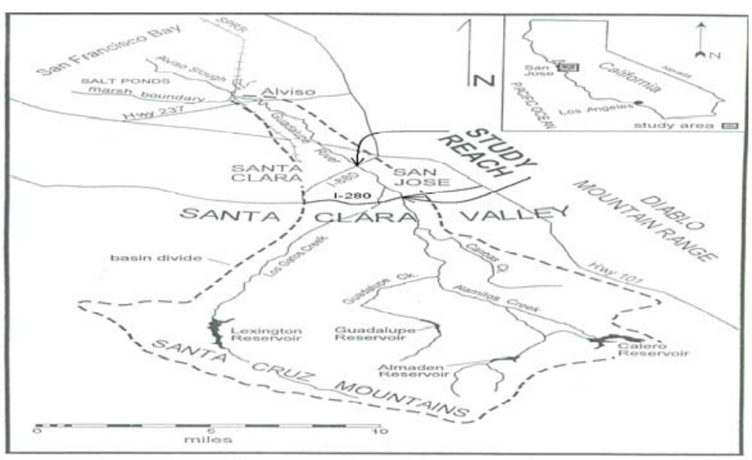


**Figure 6. Study map showing major features of Guadalupe River basin**

**Knowledge base generation.** The key word for ANNs is pattern recognition. This means that performance depends on how well developed the patterns are in the knowledge base. In other words, the total length of variables is not the most important factor contributes the generalization once the system has experienced certain extreme conditions. Twenty-two storm events with peak flow higher than 600 cfs and duration from 10 hours to 5 days were selected for sedimentation simulation. Output for each event was obtained at one-hour intervals, model time. The boundary conditions for hydrographs (cfs) and sediment inflows (tons/day) were considered system inputs. The sediment-transport rating curve for the fully alluvial reach, developed using the Toffaleti-Meyer-Peter and Muller formula, was adjusted and translated to the upstream boundaries. The data from the numerical simulation for these twenty-two storm events were saved as the system outputs. Data for three cross sections near the West Bank Bench Cut were used in this study. They include sediment passing the cross section (tons/day) and changes of deposition/scour (tons) for the reach associated with each cross section. It is noted that the changes of deposition/scour were calculated by the hourly change of accumulated sediment. In this study, sand is the only calculated sediment material. Sediment passing for each cross-section as well as the deposition/scour in each associated reach shows strong distortion of amplitude and time-delay. Obviously, this is a significant nonlinear transport phenomenon.

**Demonstration example - Simulation of sediment for passing a cross-section.** The performance of system response due to boundary forcing for ANNs modeling is somewhat different from numerical simulation. Basically, the accuracy becomes lower if the response parameters, such as transport, are different. The first test case for this demonstration uses two upstream boundary conditions, flow and sediment inflow, to predict the sediment passing the first target cross-section (number 11484).

Therefore, a two-inputs/one output system is established using ANNs with Jordan-Elman recurrent neural networks training. The first 15 storm events were used to perform the training process, 3 storm events were used as the cross-validation, and the remaining 4 storm events were used as the prediction. The extremely low mean-square-error obtained from the learning curve (Figure 7) after about 100 iterations for both training (CC= 0.96 and NMSE= 0.075; Figure 8) and cross-validation (CC= 0.97 and NMSE= 0.066) processes indicated a no over-trained and excellent result. This excellent agreement also is found in the prediction (CC= 0.98 and NMSE= 0.0041) obtained (CC= 0.96 and NMSE= 0.075; Figure 9). The result indicates that with very minimum training examples, the neural networks can produce high accuracy prediction and quick response time (10 seconds training time for this case).

Less excellent prediction results were obtained from the other two cross-sections (CC=0.902 and CC=0.874). This poorer result might be attributed to the strong nonlinearity of the HEC-6W data. It means other activation functions (transfer functions) and higher order of hidden layers and nodes need to be considered.

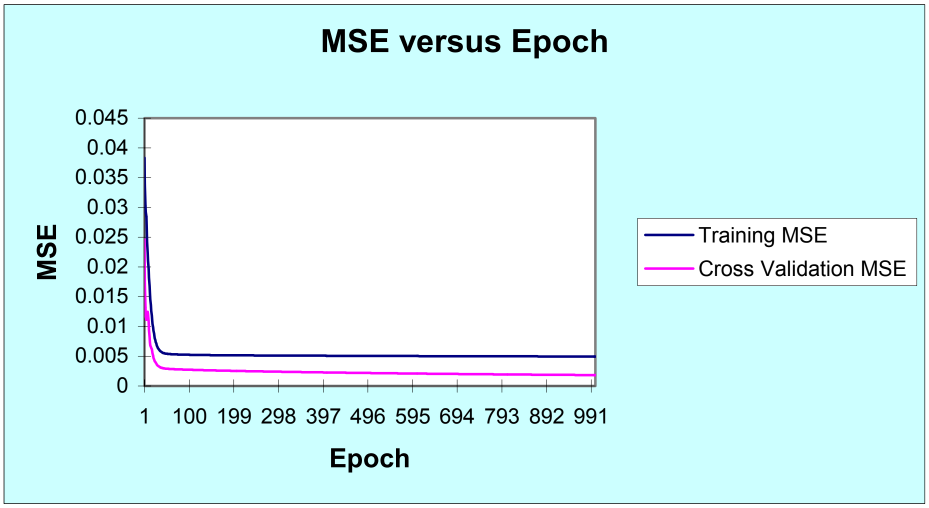


**Figure 7. Learning curve for passing sediment of cross-section 11484**

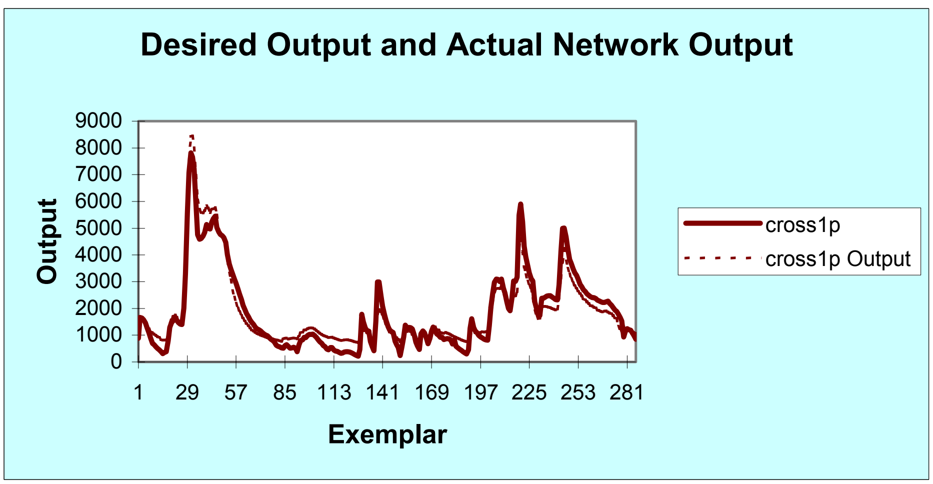


**Figure 8. Training results for passing sediment of cross-section 11484. *It is noted that the dashed line shows the neural networks output and the solid line represents the numerical model output.***

## Technical Summary and Conclusions

The performance of ANNs simulation for this tidal wetland study shows low reliability for water surface elevation, water depth, and velocity from the numerical simulation results. It is mainly due to the wet/dry characteristics of the tidal wetland, where the dry land condition cannot be represented by general external conditions.

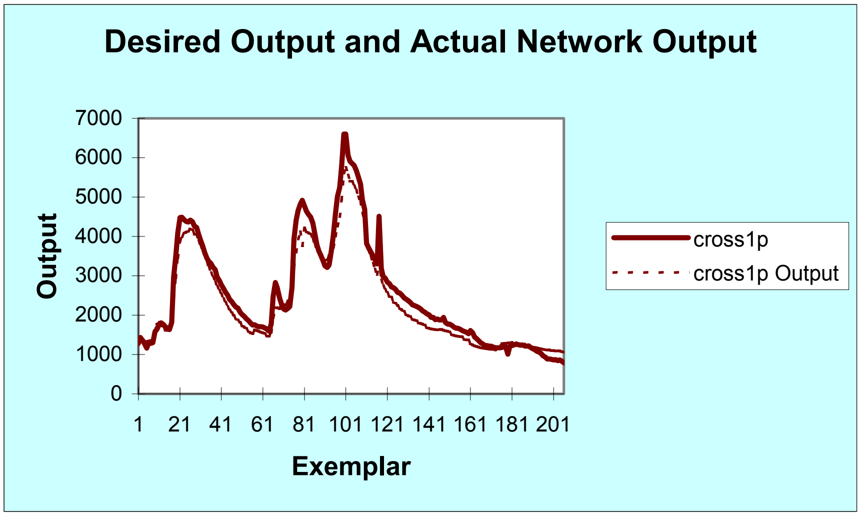


**Figure 11. Prediction results for passing sediment of cross-section 11484**

However, good results are found for the response of surface elevation (water depth) in the Upper Hudson River from long travel signals in ocean. A two-step ANN procedure, which uses surface slope from the surface elevation from neighboring nodes, can produce a good velocity simulation.

A neuro-numerical model approach was used to perform the river sedimentation simulation. The quick response time benefit will increase if an interface between numerical output and the input structure of ANNs software is available. In addition, this benefit will be more observed when this approach applies to a large-scale, multidimensional scheme, and high-density numerical sediment model. This application shows the sediment transport past a cross-section from neuro-numerical modeling approach receives better results than the estimation of deposition/scour from a river reach. This could be attributed to the differential representation of output functions. Testing higher nonlinear transfer functions and high order hidden layers, particularly for the output functions, which further far away from the forcing functions, could improve performance. More storm events produce more machine-learning experience, which is critical to increased performance reliability.

A neuro-numerical model approach can compensate for the deficiency of a numerical simulation in the processes of hydrodynamic modeling. The benefits of using this approach are to significantly reduce the computational burden required for achieving management goals, to provide an error correction for the numerical model simulation, and to provide better results for a larger domain real-time/near real-time forecasting system. However, the accuracy heavily depends the spatial scale of the response. The Jordan-Elman recurrent algorithm produces the best results because not only can it address the nonlineary but can also address the time-delay problem for the temporal and spatial variations.

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